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SYSTEMATIC REVIEW: COMPARISON OF ARTIFICIAL INTELLIGENCE METHODS FOR PAIN DETECTION

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Abstract

Objective pain detection remains a major challenge in healthcare because conventional assessments rely on subjective self-reports. Advances in artificial intelligence (AI) have enabled more objective approaches by analyzing biological signals and human expressions. Facial expressions and functional Near-Infrared Spectroscopy (fNIRS) are widely studied due to their complementary characteristics. Facial expressions are non-invasive, easy to capture, and strongly associated with visible pain responses, making them suitable for real-time applications. In contrast, fNIRS measures brain activity related to pain perception, providing a more objective physiological perspective. This study follows PRISMA guidelines for systematic literature review. Studies were identified from major databases, screened for relevance, assessed for eligibility, and included for final analysis. A total of 45 studies were selected. Previous research shows that AI, especially deep learning, is effective in analyzing facial expressions and fNIRS signals for pain detection. However, few studies systematically compare these modalities in a unified framework. This review highlights a shift from single-modality to hybrid and multimodal approaches integrating facial and fNIRS data. Deep learning models, particularly CNNs for facial analysis and hybrid machine learning–deep learning methods for physiological signals, dominate recent studies. Multimodal fusion consistently outperforms single-modality approaches, improving accuracy and robustness in pain detection tasks.

Keywords: *Pain Detection, SLR, Facial Expression, AI*

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1. INTRODUCTION

Pain is a biological and psychological response that is subjective in nature, making its assessment often inaccurate when relying solely on verbal reports or visual observation by healthcare professionals [1]. Traditional methods, such as numerical pain scales or behavioral observation, depend on patient perception and clinician interpretation, which can introduce bias [2]. This issue becomes even more challenging when assessing pain in patients with communication limitations, such as infants, elderly individuals with cognitive impairments, or critically ill patients [3]. Therefore, a more objective, consistent, and standardized approach is needed to detect pain conditions.

The development of Artificial Intelligence (AI) technology has opened new opportunities in automatic pain detection. One rapidly growing approach is brain signal analysis using functional Near-Infrared Spectroscopy (fNIRS). Research conducted by Fernandez Rojas *et al.* demonstrated that machine learning can identify pain biomarkers from fNIRS signals with a high level of accuracy, reinforcing the potential of this technology as an objective indicator of pain [4]. On the other hand, facial expression analysis has also become a popular method for pain estimation. Shier and Yanushkevich applied AI techniques for facial expression recognition and pain intensity classification, achieving stable performance in detecting micro-expression patterns that are difficult for humans to recognize [5].

In addition to traditional machine learning methods, deep learning approaches demonstrate superior performance in capturing complex patterns within neural and physiological data. Fernandez Rojas *et al.* conducted an empirical comparison of various deep learning models for pain decoding using fNIRS signals, and the results showed that certain models were significantly more effective in recognizing brain activity patterns associated with pain stimuli [6]. These findings confirm that the application of deep learning can improve the accuracy of pain detection systems.

Although numerous studies have been conducted on AI-based pain detection, most of them focus on a single method or a single type of data. There is still no systematic review that comprehensively compares the effectiveness of various artificial intelligence methods for pain detection within the most recent research period. Therefore, this study employs a Systematic Literature Review (SLR) approach to identify, analyze, and compare artificial intelligence methods used in pain detection based on scientific journals published between 2015 and 2025, with sources obtained from Scopus and Google Scholar through the Publish or Perish (PoP) application.

2. RESEARCH METHOD

This research was designed using the Systematic Literature Review (SLR) method to examine, compare, and synthesize findings from various scientific journals regarding artificial intelligence (AI) methods for human pain detection. The SLR method was chosen because it provides a comprehensive, structured, and reproducible approach for analyzing available scientific evidence. The methodology follows general principles of systematic research, including evidence-based review procedures and process transparency as described in methodological literature [7]. In this study, the SLR protocol follows the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, which consists of four main stages: Identification, Screening, Eligibility, and Inclusion. The Identification stage involves collecting all relevant studies from selected databases. The Screening stage removes duplicate records and filters studies based on titles and abstracts. The Eligibility stage evaluates full-text articles based on predefined inclusion and exclusion criteria. Finally, the Inclusion stage determines the final set of studies that are used for analysis and synthesis. Figure 1 illustrates the research methodology steps applied in this study.

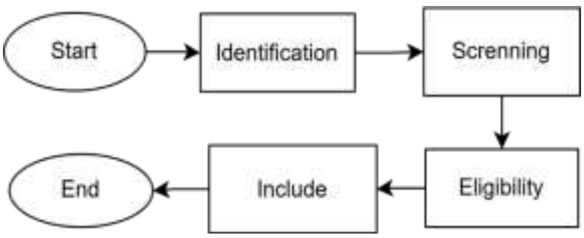

Figure 1. Research Method

2.1 Identification

The first stage is identifying the research objectives, which serve as the foundation for the literature search and selection process. This study reviews and compares various AI-based human pain detection methods from existing research to identify:

- The most commonly used AI methods in pain detection research.
- The types of data or signals used in pain detection studies.
- The performance of different AI methods in detecting human pain levels

2.2 Screening

In the screening stage, the literature search results were retrieved from two major academic databases, namely Scopus and Google Scholar. The search was limited to publications published between 2015 and 2025. At this stage, several keyword combinations were used to identify potentially relevant studies, including “pain detection”, “pain assessment”, “artificial intelligence”, “machine learning”, “deep learning”, “physiological signals”, “facial expression”, “fNIRS”, “EEG”, and “automatic detection”. These keywords were combined using Boolean operators such as AND and OR to obtain more relevant and comprehensive search results related to AI-based human pain detection. The retrieved studies were then filtered by removing irrelevant records based on titles and abstracts to ensure only potentially eligible studies were carried forward to the next stage of the PRISMA process.

2.3 Eligibility

In the eligibility stage, full-text articles were reviewed in detail to determine their suitability based on predefined inclusion and exclusion criteria. Inclusion and exclusion criteria are used to determine which studies are eligible to be analyzed in this research. These criteria ensure that only relevant and high-quality studies are selected for further analysis. Studies are included in this research if they meet the following requirements: Published in peer-reviewed scientific journals.

- Published between 2015 and 2025.
- Utilize Artificial Intelligence, Machine Learning, or Deep Learning methods for pain detection or classification.
- Use physiological signals, facial expression data, or multimodal data.
- Written in English or Indonesian.

Studies are excluded if they meet the following conditions:

- The study is a review, survey, systematic literature review, or conference abstract without complete experimental results.
- The study does not directly use Artificial Intelligence or Machine Learning methods for pain detection.

- The study does not provide model evaluation results.
- The study has limited scientific contribution or insufficient methodological detail.

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2.5 Included

In the included stage, only studies that fully met all eligibility criteria were selected for final analysis. These studies represent the final set of articles included in the PRISMA review process. From the selected studies, relevant data were systematically extracted to support further analysis. The extracted information includes:

- Research title and authors
- Publication year
- Dataset or type of signal used (fNIRS, EEG, facial expressions, etc.)
- Artificial Intelligence methods used
- Research objectives and model approaches
- Evaluation methods used
- Main results (accuracy, F1-score, sensitivity, etc.)

The data extraction process followed general guidelines for systematic data extraction in PRISMA-based reviews to ensure consistency and reliability of the collected information. After data extraction, the collected studies were analyzed to identify patterns and summarize findings from previous research. The analysis was conducted using the following approaches:

- Descriptive Analysis

This analysis describes the distribution of studies based on publication year, type of signal used, and AI techniques applied.

- Comparative Analysis

This analysis compares the performance of various AI methods in several pain detection domains, such as: facial expression analysis (e.g., CNN-based methods), physiological signal analysis (e.g., fNIRS or EEG), multimodal approaches that combine facial and physiological data

- Narrative Synthesis

Narrative synthesis is conducted to summarize research findings and identify research trends, strengths, limitations of previous studies, and potential future research opportunities.

3. RESULTS AND DISCUSSION

3. 1 Research Results

This section presents a synthesis of objective data systematically extracted from 45 primary literature on the implementation of Artificial Intelligence (AI) in pain detection over the last decade (2015–2025). The results are comprehensively articulated based on three fundamental parameters: the chronological dynamics of publications to map research trends, the characterization of data modalities to identify dominant biomarkers, and a comparative analysis of algorithm performance to determine the effectiveness of the implemented predictive models.

1. Annual Publication Trends

Based on the bibliometric analysis, research on automated pain detection has experienced notable fluctuations over the past decade, yet it maintains a significant long-term upward trajectory. As illustrated in Figure 2, the period between 2015 and 2023 saw a varying number of publications, with a prominent peak in 2020 and 2022. This inconsistency may reflect the early experimental phases of different signal modalities, such as fNIRS and EEG, before they reached a standardized implementation in clinical AI.

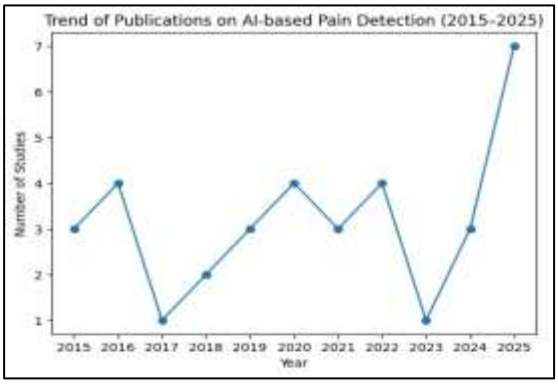

Figure 2. Trend of Publications on AI-based Pain Detection (2015–2025)

A major turning point is observed in the 2024 to 2025 period, where the number of studies surged to its highest point, reaching 8 publications in 2025. This sharp increase correlates with the rapid maturity of Deep Learning (DL) architectures and the integration of multimodal data fusion techniques. Furthermore, the rising clinical demand for objective, non-invasive monitoring systems to replace subjective self-reporting scales has driven researchers to leverage more sophisticated AI models. This trend suggests that the field is moving toward a more stabilized and intensive research phase, focusing on real-time application and higher diagnostic accuracy.

2. Distribution of Data Modality

The characteristics of the data used in the literature vary widely, ranging from visual manifestations to electrophysiological signals.

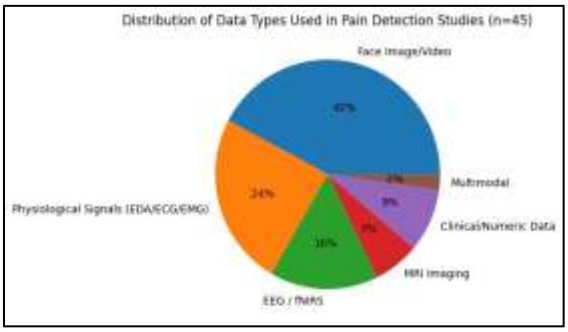

Figure 3. Distribution of Data Types Used in Pain Detection Studies (n=45)

Figure 3 shows the distribution of data types used in 45 pain detection studies. Facial expression data is the most dominant modality, accounting for 42% of the studies. Physiological signals such as EDA, ECG, and EMG represent 24%, while neurophysiological signals including EEG and fNIRS contribute 16%. Clinical or numerical data, such as self-reported pain scores, account for 9%, and MRI-based studies represent 7%. Only 2% of studies use multimodal data. Overall, facial expression remains the most widely used approach, while physiological and neurophysiological signals are increasingly explored due to their objectivity and potential for automated pain assessment.

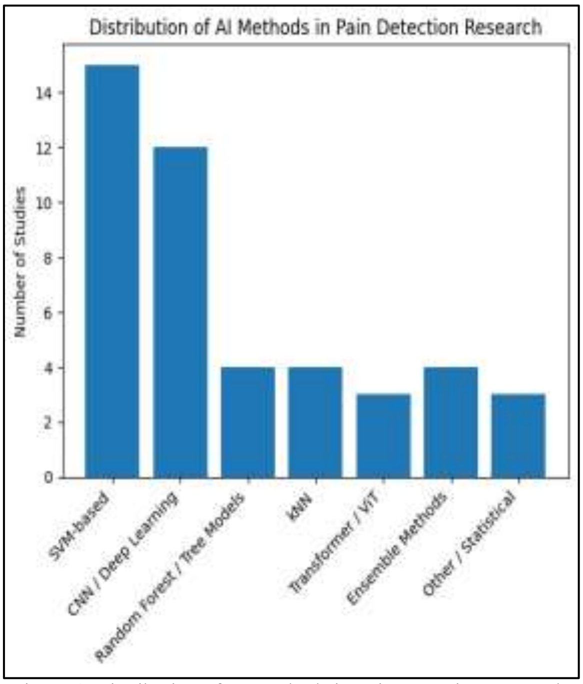

Figure 4. Distribution of AI Methods in Pain Detection Research

3. **Comparison of Algorithm Performance and Architecture**

Research over the last decade has shown a paradigm shift from conventional machine learning methods to more complex architectures.

As illustrated in Figure 4, Support Vector Machine (SVM) is the most widely used algorithm, applied in 15 studies, due to its robustness in handling high-dimensional datasets with limited samples. However, there is a clear shift toward Deep Learning (DL) models such as CNN, CNN-LSTM, and Vision Transformers, which generally achieve better performance by automatically extracting complex features. These DL approaches are particularly effective for EEG-based analysis and can reach very high accuracy levels in some studies. Overall, SVM remains a strong baseline, while Deep Learning represents the current state-of-the-art in pain detection.

In addition to the synthesized findings, a detailed overview of the included studies is presented in Table 1, which summarizes the journal characteristics. The table outlines essential attributes of each study, including methodological approaches, data sources, and evaluation outcomes, to facilitate a clearer comparison across the literature.

3. 2 Discussion

This section discusses the key findings of the systematic review by interpreting the results presented in the previous section in a broader scientific and clinical context. The discussion aims to critically analyze the implications of the identified trends, data modalities, and algorithmic performance in AI-based pain detection. In addition, this section highlights the relevance of these findings to current clinical practices, explores existing research gaps, and outlines potential directions for future studies

1. **Prisma Result Overview**

Based on the PRISMA selection process, a total of studies were identified from Scopus and Google Scholar databases. After removing duplicates and applying inclusion and exclusion criteria, only eligible studies were retained for final analysis. The screening process resulted in a final set of 45 studies included in this review. From the identification stage, a larger number of records were initially retrieved. During screening, irrelevant studies based on title and abstract were removed. In the eligibility stage, full-text assessment further excluded studies that did not meet methodological requirements or lacked evaluation results. Ultimately, 45 studies were included for qualitative and quantitative synthesis in this review.

2. **Issue Summary Overview**

This systematic review confirms that AI-assisted pain detection is being developed to address the subjectivity of human assessments, such as the Visual Analogue Scale (VAS), which is difficult to apply to non-communicative patients or neonates. A key issue identified is the need for standardized biomarkers that can be continuously measured without biased manual intervention

Table 1. Journal Characteristics

No	Ref	Data Types	AI Methods	Research purposes	Key Results
1	[8],[13], [19], [25], [31], [32], [35], [43], [44], [36]	Physiological signals (EDA, ECG, EMG, GSR, BVP)	SVM, RF, XGBoost, CNN, LSTM, Transformer, Ensemble	Developing objective pain detection systems using physiological signals	Accuracy 80–90%, best 90% (MTVSymp + SVM), sensitivity ~78.9%
2	[10], [14], [4], [38], [41], [49], [47]	Brain signals (EEG, fNIRS)	ANN, CNN, RNN, LSTM, SVM, Ensemble	Detecting and classifying pain using neural activity signals	Accuracy up to 99%, AUC up to 0.97; high potential but complex data processing
3	[9], [11], [18], [21], [29], [33], [37], [39]	Face Video	SVM, RF, AdaBoost, CNN, Feature-based methods	Developing automatic pain detection systems using facial expressions in video	Accuracy ranges from 72% to 96%; strong performance in controlled environments
4	[12], [15], [17], [16], [28], [30], [34], [40], [50], [51]	Facial images	SVM, CNN, Vision Transformer, Fusion models	Developing pain detection and intensity estimation using facial images	Accuracy ranges from 56% to 98.79%; deep learning (CNN/ViT) achieves highest performance
5	[23], [24], [20], [42], [48], [46]	MRI & clinical data	CNN, statistical modeling, regression	Supporting clinical diagnosis and validation of pain conditions	High diagnostic performance (AUC up to 0.917), strong correlation with clinical metrics
6	[22], [45], [26], [27]	Multimodal & alternative data (video + physiological, biomechanical, animal data)	SVM, RF, ANN, Fusion models	Exploring multimodal and non-traditional approaches for pain detection	Accuracy up to 96.43%; multimodal approaches improve robustness and generalization

3. Issue Summary Overview

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4. Analysis of Main Findings

A synthesis of the reviewed literature shows that the integration of Deep Learning provides fundamental advantages in identifying non-linear and complex pain manifestation patterns compared to manual feature-based methodologies. This architectural superiority is reflected in the ability of Convolutional Neural Networks (CNN) to automatically and deeply extract hierarchical features directly from raw facial image data, which minimizes the subjective bias of traditional feature engineering. Furthermore, the use of Long Short-Term Memory (LSTM) units and Transformer models has proven highly effective in capturing temporal dynamics and long-term dependencies in time-series physiological signal data. Furthermore, these findings confirm that the Multimodal Fusion approach, which synergizes visual facial expression data with biological signals such as EDA, ECG, or EEG, is empirically able to improve the detection performance and reliability of the system compared to the unimodal approach. This cross-modality synergy allows the model to perform data compensation (data redundancy), where the limited information in one sensor can be covered by other sensors, resulting in a more robust and accurate pain assessment system for clinical needs.

5. Implications for Clinical, Academic, and Regulatory Practice

This research identified several gaps that need to be addressed. Most studies still rely on controlled laboratory datasets, resulting in limited clinical validation in real world settings. Future research should focus on personalizing AI models that adapt to individual variations and on cross dataset testing to ensure model generalizability.

4. CONCLUSION

A systematic literature review based on the PRISMA framework was conducted on 45 selected articles published between 2015 and 2025. The PRISMA selection process began with identification from Scopus and Google Scholar databases, followed by screening of titles and abstracts, eligibility assessment based on full-text review, and final inclusion of studies that met all predefined criteria. After duplicate removal and filtering, a total of 45 studies were included for final analysis. The results of this PRISMA-based review confirm a paradigm shift in pain detection from subjective assessment toward AI-based objective systems. The included studies show that facial expressions and biophysiological signals (EDA, ECG, EMG) are the most widely used modalities, while neuroimaging techniques such as EEG and fNIRS demonstrate the highest reported accuracy, reaching up to 99% in some studies. Methodologically, there is a clear evolution from traditional Machine Learning approaches toward advanced Deep Learning architectures such as CNN, CNN-LSTM, and Vision Transformers. The integration of multimodal approaches has been shown to significantly improve system reliability in mapping complex pain-related patterns. Based on the PRISMA review findings, future research is recommended to move beyond literature-based studies and focus on experimental validation using real-world clinical data. The development and testing of AI-based pain detection systems using physiological, visual, or multimodal data are essential to improve clinical applicability. In addition, multimodal approaches should be prioritized due to their superior accuracy and robustness compared to unimodal systems. Future studies are also encouraged to compare multiple AI techniques such as Convolutional Neural Networks (CNN), Support Vector Machines (SVM), and Random Forest using larger and more diverse datasets to enhance generalizability. Real-time evaluation and clinical deployment testing are crucial to ensure practical implementation in healthcare settings.

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